What Top Management Thinks About the Benefits of Hard and Soft Manufacturing Technologies

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***Abstract*—Each year, billions of dollars are spent by U.S. manufacturers to acquire hard and soft manufacturing technologies. Hard technologies are bundle of equipment, computer hardware and software such as computer numerical control, computer-aided manufacturing, robots, etc. In contrast, soft technologies are manufacturing techniques and know-how such as just-in-time, total quality management, statistical quality control, etc.—hardware is not essential to their successful use but can enhance their scope and effectiveness.**

This large empirical study of 1042 U.S. manufacturing plants develops a model to study the impact of manufacturing technology use on various performance measures; this study provides first evidence from the field that soft manufacturing technologies have many times the measurable effects of hard technologies on product, process, and business performance. Further, the effects of technology use are enhanced by the *skilled use* of technology. Implications for research and public policy are addressed.

This paper has found that, in the opinion of top management in manufacturing firms, soft technologies have an impact on 1) shop floor performance; 2) product line breadth; and 3) growth and profitability. These finding should make the investment in soft technologies easier to justify. If top management controls the purse, and if it sees a link between investment in soft technology and tangible benefits in these three areas, getting top management to invest in soft technology should be easier. Before deciding on requests for investments in soft technologies, we hope top managers would seriously consider the findings of this paper.

***Index Terms*—Growth and profitability, hard technologies, investment justification, manufacturing technology, plant performance, product line breadth, shop floor performance, soft technologies, strategic performance.**

I. INTRODUCTION

An UNDERLYING premise among practitioners and researchers is that the use of advanced manufacturing technologies (AMT) enhances manufacturing firm performance. The usage of the term "advanced manufacturing technologies" is associated with hardware-intensive technologies such as computer-aided manufacturing (CAM), computer numerical control (CNC), flexible manufacturing systems (FMS), and robots, as well as manufacturing techniques such as just-in-time (JIT), statistical quality control (SQC), etc. While macroeconomic studies have addressed this issue for some time, microeconomic evidence to support this view is trickling in through empirical studies reported by operations management researchers only within the last ten years [6], [12], [14], [15], [16], [21], [29], [33]. In addition, training, which is an essential part of continuous process improvement, lean manufacturing and soft technology use, has been linked to improved manufacturing performance [1], [11], [23].

Field studies in this area are limited because they have encountered challenges in linking manufacturing technology use with product performance (e.g., product line breadth), process performance (e.g., shop floor performance), and business performance (e.g., growth and profitability). The major reasons for this difficulty stem from challenges to the measurement of technology use and its effects and data availability.

The importance of understanding the link between technology use and plant performance are many; the most important being, several billion dollars are invested each year by manufacturing firms in the hope of improving performance and competitiveness. Such investments are vital to over 300 000 manufacturing plants in the U.S.; the five large groups of industries (SIC 34–38) covered by this study alone have over 42 000 plants [10], and their total shipments exceeded \$1.3 trillion at the time of this study [30].

This large empirical study of 1042 U.S. manufacturing plants, develops a path analysis model to study the impact of manufacturing technology use on various measures of performance; this study provides first evidence from the field that soft manufacturing technologies have many times the measurable effects of hard technologies on product, process, and business performance. Further, the effects of technology use are enhanced by the *skilled use* of technology. Implications for research and public policy are addressed.

II. RESEARCH BACKGROUND

The premise of this paper is that investments in manufacturing technology are justified by tangible benefits that enhance performance. This section addresses some of the more recent research on the subject and the issues surrounding the use of manufacturing technologies and their effect on plant performance.

Flynn *et al.* [15] provide a brief overview of three of the studies conducted as part of World Class Manufacturing project, dealing with manufacturing process innovation; the relationship between quality practices and performance; and the relationship between total quality management (TQM) and JIT. Each of these studies highlights specific manufacturing practices, which are related to performance, as well as relevant infrastructure

Manuscript received October 1, 2003; revised June 25, 2004. Review of this manuscript was arranged by Department Editor J. K. Liker. This work was supported in part by the National Science Foundation (NSF) and the Manufacturing Institute of the National Association of Manufacturers.

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Digital Object Identifier 10.1109/TEM.2004.835090

characteristics. The authors considered manufacturing process innovations such as TQM, JIT, cellular manufacturing, supplier reduction, employee involvement, computer-aided manufacturing (CAD)/CAM and manufacturing strategy. Additional evidence on the relationship between TQM and JIT performance is found in [14]. Further, Flynn *et al.* [16] provide evidence of the impact of quality management practices on performance and competitive advantage.

Henderson *et al.* [21] have shown that the *skilled use* of hard and soft technologies "produces significant improvements in a composite measure of nonfinancial manufacturing performance and ROI."

Measuring and assessing the effect of manufacturing technology on performance is a challenge because the effect of technology use can be diffused, distributed, and diverse. Therefore, no single measure of performance is appropriate in capturing the effect of technology use on performance. Consequently, we use three kinds of performance in manufacturing firms. We study the effect of manufacturing technologies on: 1) shop floor performance; 2) product line breadth; and 3) strategic performance.

A. Shop Floor Performance

When soft technologies such as JIT practices are implemented, performance on the shop floor improves in many dimensions which are measurable; e.g., reduced waste, lead-time, inventory, and cost [12], [19].

B. Product Line Breadth

The ability to sustain a broad product line gives the company several competitive advantages. It enables the company to benefit from economies of scope [4]. Two studies in OM have spot-lighted the value of product line width to manufacturing firms: Kekre and Srinivasan [22, p. 1227] and Swamidass *et al.* [34]. Kekre and Srinivasan found that "a broader product line leads to a higher market share, as well as to increased profitability." Swamidass *et al.* reported that with the increase in product lines, inventory turns increased and sales per employee (a measure of efficiency) also increased.

C. Strategic Performance

Growth and profitability are two of the commonly used important strategic performance measures. Focused production and reduced manufacturing cycle times are also of strategic value to manufacturers. From the perspective of researchers, as well as practitioners, investments in manufacturing technologies are expected to contribute to strategic performance.

D. Technologies Studied

Some studies tend to treat hard technologies alone as manufacturing technologies. Gerwin and Kolodny [18] define manufacturing technology to be "…more than machines used in production—it is a system of hardware, software (codified procedures), and humans…," and informal procedures and know-how stored in human memories. Yet, the lists of manufacturing technologies considered by researchers in the late 1980s and 1990s have either excluded all soft technologies, or included a limited number of soft technologies such as materials requirements planning (MRP) or MRP II[1] [10], [18], [20], [28].

Hard and Soft Technologies: In this paper, manufacturing technologies are classified into two groups: hard and soft technologies. Similar classifications of manufacturing technologies could be found in recent studies [32], [35]. Today, hard technologies are complex bundle of equipment, computer hardware and software; CNC, CAD, CAM, computer-integrated manufacturing (CIM), local area network (LAN), automated inspection, robots, automated guided vehicles (AGVs), and FMS are hard technologies included in this study. In contrast, soft technologies are manufacturing techniques and know-how such as JIT, TQM, MRP I, MRP II, manufacturing cells, and SQC—equipments and computers are not essential to their successful use but can enhance their effectiveness. We recognize that while some technologies are clearly hard technologies and others are clearly soft technologies, some technologies fall in a gray region between the two extremes. We have exercised some judgment in classifying a technology in the gray region into one or the other. The technologies investigated in this study cover most of the hard technologies covered by the U.S. Bureau of Census (BOC) study [9], [10] plus some not covered by the BOC study. Particularly, the six soft technologies investigated here are not included in the BOC study.

E. Issues in Technology Measurement

The measurement of AMT use is fraught with numerous problems. See Boyer and Pagell [7] for an extensive discussion of the subject. They cover major issues concerning AMT measurement including content validity, criterion validity, and other methodological issues.

Boyer and Pagell offer an in-depth critique of a perceptual measure of AMT used by Boyer *et al.* [6]. They critique the measure based on a questionnaire that asked managers to "Indicate the amount of investment your manufacturing plant has in the following activities (Likert scale ranging from 1=no investment, to 4=moderate investment, to 7=heavy investment)" [6, p. 366]. Their criticism being, "Measures such as these that tap the level of investment in a technology as being from low to high suffer from some shortcomings." However, they note that the use of actual investment in technology in terms of dollars or some other currency is not a good substitute either because "it is difficult to decipher" [6, p. 366]. Therefore, they conclude, "…Likert scale measures of AMT exist because they work, …. However, …even though they have good psychometric properties, they may not be completely addressing the factors they are supposed to address" [6, p. 367].

Given that likert-type scales have a proven track record in research, have good psychometric properties, and the alternative measurement of *actual investment* may have dubious validity issues, the measure used by this study does not deviate from the oft-used Likert's model. In this study of 17 technologies (described later), each of the 17 technologies are rated on a scale, 1=do not use, 2=used with some skill, 3=used with moderate skill, and 4=used with extreme skill. This is not

[1]See Appendix I for a description of 15 different manufacturing technologies investigated.

a perfect measure for some of the reasons described in the paper by Boyer and Pagell [7], but it overcomes the limitations of measuring the *investment in AMT* that Boyer, *et al.* [6] mention. Skilled use of a given technology is associated with the length of experience with the technology, the training and retraining of operators using the technology, a good fit between the computer software and hardware, the fit between the technology and the rest of the production system, and the like. "Unskilled" use of a technology would negate the potential for gains in productivity, quality, and speed of production a plant could realize from the use of a given technology.

The premise of this study is that, higher the *skill level in the use of a technology*, more the investment and higher the level of technology adoption by the plant. The measure of "*skilled use*" overcomes some of the measurement error introduced by plants that invest heavily into a technology but fail in their ability to adopt the technology. A recent in-depth study of technology adoption by 15 U.S. manufacturers [38] showed that some plants were slow or unsuccessful in adopting CNC equipment, robots, and ERP software in which they made substantial investments. Therefore, investment in technology does not equal automatic, successful use in manufacturing plants. Further, [36] using a multiple regression model ($R^2 = 0.28$, $p = .0001$), found that the number of benefits ascribed to a technology "improved with improved skill in technology use."

While studying technology use, the researcher is faced with the challenge of identifying a set of technologies to measure. Some may be too old, and some may be too new. With time, newer technologies need to be added and some dropped [7]. A good example of this need to keep the list of technologies dynamic is evident in the repeated studies of technology use by Swamidass (15 technologies) [36] and Swamidass (17 technologies) [37]. In the latter study, one technology was replaced and two new ones were added.

Psychometric theory advocates the use of multiple items in constructing a measure. In this regard, a measure that includes 17 technologies in this study captures the essence of technology use. In this paper, we have covered a wide range of technologies covering both older and newer technologies. It enables us to see how technology use varies from those that have become entrenched (the result of being around longer) to those that are relatively new. In this dynamic environment, where some technologies are older and others are being newly introduced, there is little consensus among researchers on the *exact list* of technologies to compare. However, we think it is a healthy sign that there is considerable overlap among the technologies on the lists of technologies being investigated by a diversity of researchers. The overlap among the various lists speaks for the validity of the core items in these lists.

III. Method

A. Sample

This paper investigated technology use in discrete products manufacturing industries covered by SIC 34–38 (see below for a description of these industries). These industries are often grouped together in manufacturing technology studies [10] because the processes they use are similar, while their products may be very different. The industries in SIC 34–38 produce discrete products as opposed to commodity products such as gasoline, sugar, chemicals, and the like. The industries covered by these classification are the following:

SIC 34 Fabricated metal, except machinery.
SIC 35 Industrial and commercial machinery, computer equipment.
SIC 36 Electrical, other electrical equipment.
SIC 37 Transportation equipment.
SIC 38 Measurement instruments, photo goods, watches.

Data on manufacturing technology use were collected from manufacturing plants (as opposed to firms) using a survey questionnaire. The questionnaire was first developed for a pilot study conducted in 1990, in which 385 manufacturers participated. Based on the pilot study, a revised questionnaire was developed and tested with managers in 1993. The survey questionnaire on manufacturing technology use was mailed in the later part of 1993 to all 4453 members of National Association of Manufacturers (NAM), who belong to the SIC classifications 34–38. One reminder in the form of a post card was sent ten days later followed by a duplicate of the questionnaire and cover letter a few weeks later.

Since technology use within the various plants of a single firm may vary substantially between plants due to the nature of products produced, the age of the plant, etc., the questionnaire requested multiplant manufacturers to provide data from any one of their plants.

Nonresponse Bias: To examine nonresponse bias, if any, a split sample was developed; the first 556 responses formed the first sample, and the second 565 responses formed the second sample for a total of 1121 responses. The resulting response rate being 25.8% including 25 unusable responses and three that arrived after the cutoff date. Details of data collection and sample validation are described in Appendix II. The two split samples are very similar, thus evidence in Appendix II reveals no particular bias in the sample.

Of the 1121 responses, 79 that did not belong to SIC 34–38 were excluded from further analyses resulting in a *sample of 1042 plants*. Responses were from the top management of plants; 86% of the respondents reported their titles to be vice-president or higher including owner, chief executive officer, president, etc.

IV. Model of Technology Use and Performance

Fig. 1 shows a path analysis model of technology use, which has two components: technology inputs and the resultant benefits. The model is discussed in this section after a discussion of the variables in the model.

A. Variables and Measures

Technology Measures: The model in Fig. 1 is composed of two technology variables, TECSUM (H) and TECSUM (S), which stand for the **weighted sum** of hard and soft technologies used in a plant, respectively. Respondents were asked to "rate your plant's skill level in the use of following technologies." The options were extremely skilled use (weight $= 3$), moderately skilled use (weight $= 2$), used with some skill (weight $= 1$),

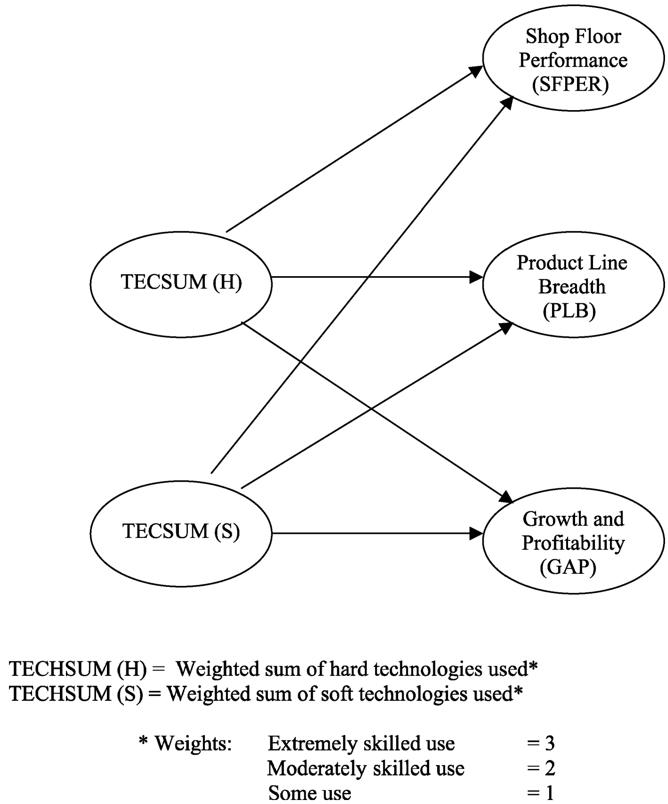

Fig. 1. Model of hard and soft technologies on performance measures.

and do not use (weight $= 0$). Given that nine hard technologies were included in the study, the score for TECSUM (H) ranged from 0 to 27. Further, given that six soft technologies were included in the study, the score for TECSUM (S) ranged from 0 to 18.

As mentioned, the weighting system used here assigns a weight of 3 to extremely skilled use and a weight of 1 for mere use of the technology. The implications of this is that a plant merely using 15 different technologies would have a total technology use score of 15, which would be the same for a firm that uses five different technologies with extreme skill.

Performance: One of the hurdles to studying the impact of technology use on performance is the difficulty in measuring and quantifying the benefits of technology use because there are so many. Respondents were given a list of 13 possible benefits and were asked to check all those benefits, in which they made "significant progress ... as a direct result of our investment in one or more" of the technologies listed: a) zero defects; b) zero inventory; c) zero setup time; d) sole sourcing; e) lot sizes of 1; f) mixed-model lines; g) focused production; h) reduced manufacturing cycle-time; i) increased product line; j) increased number of models; k) more frequent introduction of new models; l) return on investment; and m) growth in market share. These items fall into three performance categories: 1) shop-floor performance—includes items a), b), c), d), and e) above; 2) product-line breadth—includes items f), i), j), and k); and 3) strategic—includes items g), h), l), and m). Note the fact that the performance items use binary scales (yes or no). The reason for using a binary scale was that we could get top-level managers to check yes/no on as many as 13 performance measures. Comparable studies rarely gather data on so many performance measurement items.

The correlations among the 13 items were considered and we grouped them into three performance factors consistent with our earlier conceptualization. The performance factors are made of a reduced set of items as shown below. These performance factors which are based on the sum of item scores are used in all subsequent analyses.

Product Line Breadth (PLB):
- increased product line;
- increased number of models;
- more frequent introduction of new models.

Shop Floor Performance (SFPER):
- zero inventory;
- zero setup time;
- lot size $= 1$.

Growth and Profitability (GAP):
- return on investment;
- growth in market share.

B. Path Analysis Model

Using the adage "reality must be reduced to manageable proportions whenever we construct models" [27], a parsimonious set of variables is used to model the relationship among manufacturing technology and key performance variables in Fig. 1.

In Fig. 1, the line joining two variables represents a hypothesized relationship between the two variables, and the arrowhead expresses the direction of the relationship; the arrow originates at the independent variable and ends at the dependent variable.

While the model is a study of the effect of the use of manufacturing technologies on performance, the model does account for variances in performance due to factors not explicitly considered here; this is important because manufacturing technology use may explain some of the variations in performance, but it cannot explain all the variations.

The conceptual model in Fig. 1 expresses the following hypotheses.

H1) Hard technology is significantly associated with product line breadth.

H2) Soft technology is significantly associated with product line breadth.

H3) Hard technology is significantly related to enhanced shop floor performance.

H4) Soft technology is significantly related to enhanced shop floor performance.

H5) Hard technology is significantly related to growth and profitability.

H6) Soft technology is significantly related to growth and profitability.

While hard and soft technologies are not substitutable, there may be some correlation between hard and soft technologies.

H7) Firms that use hard technologies would also use soft technologies.

TABLE I
REGRESSION EQUATIONS FOR THE MODEL IN FIG. 1
(SIGNIFICANCE IN PARENTHESIS)

SFPER = -0.015 + 0.004 **(TECSUM - H)** + 0.085 **(TECSUM - S)**		
(R^2 = 0.203)	(p=0.493)	(p=0.0001)
(p = 0.0001)		
(n = 1041)		
PLB = 0.407 + 0.008 **(TECSUM - H)** + 0.028 **(TECSUM - S)**		
(R^2 = 0.024)	(p=0.314)	(p=0.001)
(p = 0.0001)		
(n = 1041)		
GAP = 0.351 + 0.016 **(TECSUM - H)** + 0.045 **(TECSUM - S)**		
(R^2 = 0.104)	(p=0.006)	(p=0.0001)
(p = 0.0001)		
(n = 1041)		

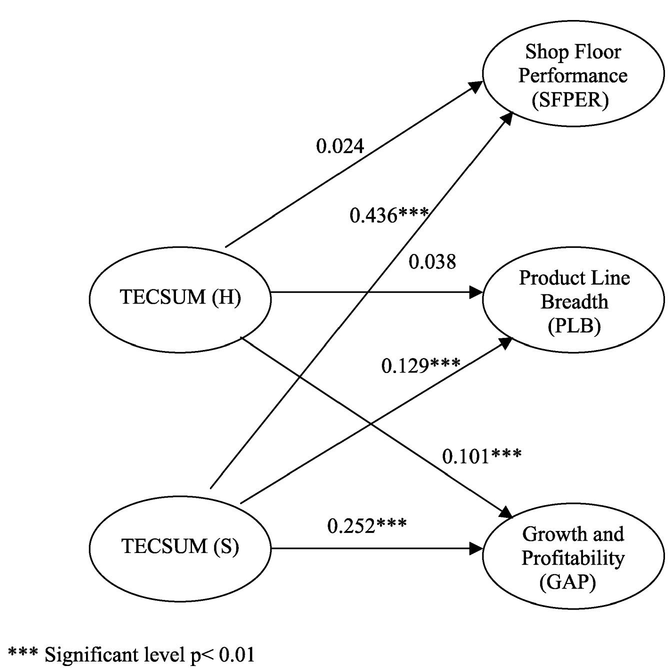

Fig. 2. Estimated model of hard and soft technologies and performance measures.

V. RESULTS

A. Plant Characteristics

The average plant had 228 employees and \$47 million in sales. When projected over all 1042 plants in the sample, total employment of all the plants in the sample is 237 439, and total sales is \$49.2 billion.

B. Model Estimation

The three equations of the model in Fig. 1 were estimated using SPSS software's multiple regression procedure with data from 1042 responding plants and the results are shown in Table I and Fig. 2. In Fig. 2, the standardized *coefficient beta* for each relationship is reported next to the line with the appropriate sign—note that Table I shows unstandardized coefficients. A coefficient beta indicates the "change in the mean of the probability distribution" of the dependent variable per unit increase in the independent variable [27]. Notable aspects of the model are the following.

1) PLB is not significantly explained ($R^2 = .024$) by the independent variables in the equation for PLB in Table I.
2) In Fig. 2, SFPER is significantly related to only soft technology ($\beta = 0.436$; $p < 0.01$) and NOT to hard technologies. An R^2 of 0.203 for SFPER in Table I suggests that almost 20.3% variation in SFPER explained by hard and soft technologies.
3) In Fig. 2, GAP is significantly related to both hard and soft technologies. Moreover, in Table I, the technologies explain 10.4% of the variation in GAP ($R^2 = 0.104$).
4) *Soft Technologies*: The model detects the stronger beneficial effects of soft technologies over hard technologies. In Fig. 2, the links between TECSUM(S) and performance variables are all significant at the 0.001 level (0.44; 0.129; and 0.252), whereas the links between TECSUM(H) and performance variables are not significant except for the link to GAP (0.101; $p < 0.001$). Thus, soft technologies such as JIT, manufacturing cells, SQC, etc., together have a stronger effect on various performance measures. This is a unique contribution of this paper, which is able to compare the differential effects of hard and soft technologies on factory performance measures. The implications of this are many including the justification of investments in soft technologies versus hard technologies.
5) Hard and soft technologies are positively correlated as hypothesized; the Pearson correlation coefficient is 0.603, $p < 0.01$. This supports Hypothesis 7.

A summary of the results of hypotheses testing is presented in Table III.

Test for JIT's Effect:[2] We dropped the item "JIT" in TECSUM (soft) and reestimated the structural equations in Table I to evaluate if JIT had any substantial effect on the dependent variable SFPER because one may think that the items making up SFPER are closely associated with JIT. Our findings showed that the change had negligible effect on the structural equations for SFPER, PLB, and GAP reported in Table I, and hypotheses tests in Table III.

C. Effects of the Skilled Use of Technology

The model in Fig. 2 and Table I account for the skilled use of technology. In order to isolate the effects of the skilled use of technologies on performance, the three equations of the model in Table I were reestimated without giving any consideration for skilled use; this was accomplished by the recoding of the technology use variables, where 1=technology is used regardless of skill; and 0=technology is not used.

Table II isolates the *increase/decrease in the effects* of technology use when skilled use is included in the model in Fig. 2 and Table I. According to Table II, skilled use of technology improves the model's ability to explain the variance in SFPER,

[2]This was suggested by a reviewer.

TABLE II
EFFECT OF SKILLED USE OF TECHNOLOGY

Independent Variable	Variance Explained by the Model		Change in Variance Explained when Skilled use is Considered
	Skilled Use Not Considered	Skilled Use Considered	
1. Shop Floor Performance (SFPER)	14.8%	20.3%	+37.16% *
2. Product Line Breadth (PLB)	2.6%	2.4% **	Negligible variance explained
3. Growth and Profitability (GAP)	8.9%	10.4%	+16.85% ***

* (20.3 – 14.8)/14.8 = +37.16%
** (2.4 - 2.6)/2.6 = -7.69%
*** (10.4 - 8.9)/8.9 = +16.85%

TABLE III
TESTS OF HYPOTHESIZED OUTCOME RELATIONSHIPS

Hypothesis Description	Standardized Parameter Estimate/ Correlation Coefficient (for H7)	t-values	Conclusion
H1: Hard technology is significantly associated with product line breadth.	0.038	1.008	H1 not supported
H2: Soft technology is significantly associated with product line breadth.	**0.129***	3.382	H2 supported
H3: Hard technology is significantly related to enhanced shop floor performance.	0.024	0.686	H3 not supported
H4: Soft technology is significantly related to enhanced shop floor performance.	**0.436***	12.668	H4 supported
H5: Hard technology is significantly related to growth and profitability.	**0.101***	2.775	H5 supported
H6: Soft technology is significantly related to growth and profitability.	**0.252***	6.891	H6 supported
H7: Firms that use hard technologies also tend to use soft technologies.	**0.603***		H7 supported

* Significant at $p<0.01$

and GAP by significant percentages; 37.2% and 16.9%, respectively. In Table II, PLB is not meaningfully explained (variance explained is $< 3\%$ in Table II) with or without the use of skilled use of technologies in the models.

Thus, the evidence here shows that the skilled use of hard and soft technologies *increases* the impact of technology use on SFPER, and growth and profitability. The models are able to show the effect of the skilled use of technologies as never before. We used a three-point scale to capture the skilled use of technologies. In the future, researchers could build on the findings of this study and develop an even more improved measurement of the effect of skilled use of technologies. Any measurement error surrounding this could be alleviated by providing a short description of what "skilled use" means.

VI. CONCLUSION

The three notable findings of this paper are 1) technology use has a tangible and measurable effect on growth and profitability; 2) soft technologies have an effect on shop floor performance, product line breadth, and growth and profitability, whereas hard technologies have negligible effect on the three performance variables considered; 3) skilled use of technology improves the model's ability to explain the variance in SFPER, and GAP by significant percentages: 37.2% and 16.9%.

In this paper, soft technologies emerge as a strong performance enhancing tool at the shop floor level, as well as at the business level, where growth and profitability are important measures. The term "manufacturing technology" is often associated with hard technologies. Therefore, a study such as this is an eye-opener. The lesson here is that, while hard technologies are appropriate for attaining certain limited goals, soft technologies have a much broader impact on the manufacturing plant. The study shows that, according to top management, who evaluated the benefits of technology use, the effect of soft technology use can be found in three performance areas: 1) SFPER; 2) PLB; and 3) GAP.

A. *Hard Versus Soft Technologies*

One limitation to remember while interpreting the findings is that top managers may have limited knowledge of the technologies and benefits ascribed to them. Our evidence shows that, based on inputs from top management, soft technologies seem to have a stronger effect on various measures of performance that we considered than hard technologies. How could we explain this? The following are potential explanations and implications, which deserve investigations in the future.

1) Hard technologies such as CAD, CNC, CAM, and others are very widely used, and their use may have matured to the point that they are essential to the success of almost all manufacturers. That is, plants can no longer be distinguished on the basis of most hard technologies used.
2) The list of benefits included in the questionnaire may not have adequately covered the benefits that are likely to be associated with hard technologies. If this were true, the benefits of hard technologies would be underestimated by the measures SFPER, PLB, and GAP. This deserves further investigation by using performance measures that capture the benefits of hard technologies.
3) Hard technologies may need the support of several complementary factors to make an effect on the performance variables that we used in our study. For example, studies by Adler [3], Buitendam [8], Lee [24], Boyer *et al.* [5], and Boyer *et al.* [6] found that successful integration and implementation of CAD, CAM, and CAD/CAM is more than a technological solution; the organizational structure, the sociopolitical environment, trust, control, and other nontechnical factors are essential to the success of these technologies.
4) Given the findings of this study that skilled use of technology better explains the variance in performance measures. Skilled use of a given technology is associated with the length of experience with the technology, the training and retraining of operators using the technology, and similar items.
5) Soft technologies such as JIT, TQM, manufacturing cells, and SQC have a sweeping impact on almost all functions in a factory, as well as suppliers and customers, and they rearrange the organizational structure, alter the control structure, etc. For example, JIT requires

suppliers to be in tune with the quality requirements and schedules of their customers. Further, TQM requires manufactures to align their organization to meet customer needs sooner and better than their competition. Thus, the implications of soft technologies may go far beyond the localized effects of CNC machines, CAM, and other hard technologies.

6) The respondents, who are part of the top management, may be more aware of soft technologies used in the plant through training programs and visibility of these programs. In contrast, hard technologies and their benefits may be less visible to top management.

B. Implications

For Investment Decisions: The evidence that soft technologies have a more significant effect on SFPER, PLB, and GAP does not mean we must tilt technology investments toward soft technologies at the expense of hard technologies. In the plants we studied, both hard and soft technologies were used simultaneously. For localized benefits in manufacturing operations, investments in hard technologies may have no substitutes. For factory-wide impact, soft technologies seem to be essential. To the practitioner, the important lesson here is that investments in hard technologies may be improper when investment in soft technologies is the need of the hour, or when investments in both are needed. For factory-wide improvements in performance measures, evidence shows that soft technologies must be a part of the investment.

The importance of the *skilled use of technologies* should not be ignored in investment decisions. There can be no skilled use of technologies without skilled employees who are trained and retrained. Evidence from outside of this study points to the shortage of manufacturing worker skill levels in the U.S. According to one estimate, "... 40% of companies have had trouble upgrading production techniques because of inadequate skilled labor," and as much as 30 million workers in the U.S. may need retraining to narrow the skills gap [25]. While enhancing the skilled use of existing investments may yield *unrealized* benefits from technologies already in use, the shortage of skilled workers may hold back manufacturers from realizing all the benefits of technology use.

For Public Policy: Policy makers have made tangible policies backed by budget appropriations to help manufacturers become more competitive through investments in manufacturing technologies [13], [17]. Certain governmental programs established through the NIST and the NSF channel funds to state and federally funded technology centers for enhancing the use of manufacturing technology in small plants. Many state and other programs target employee training to enhance the skill level of manufacturing employees. Our findings about the benefits of the skilled use of technologies lend support to these policies.

C. Significance of This Study for Investment Justification

Investment in manufacturing technology is very expensive. Often manufacturing firms are criticized for not investing in manufacturing technologies. One of the reasons for manufacturers' reluctance to invest in manufacturing technologies is that the link between investments and benefits is tenuous at best. Researchers have found it a challenge to establish a link between manufacturing technology use and plant performance metrics. This study has found that, in the opinion of top management in manufacturing firms, soft technologies have an impact on 1) SFPER; 2) PLB; and (3) GAP. These finding should make the investment in soft technologies easier to justify. If top management controls the purse, and if it sees a link between investment in soft technology and tangible benefits in these three areas, getting top management to invest in soft technology should be easier. Before deciding on requests for investment in soft technologies, we hope top managers would seriously consider what we report here about top managers' view of the benefits of technology use in manufacturing firms.

Only the Bureau of Census [10] studies of manufacturing technology employed a larger sample than this study but those studies do not investigate 1) soft technologies and 2) the skilled use of technologies. The evidence here underscores the importance of soft technologies and the skilled use of technologies.

D. New Directions for Research

This study was successful in its investigation of the effect of technology use on plant performance metrics partly because of the measures devised. However, there is room for improving the measures devised here for complex variables such as technology use, skilled use of technology, and benefits of technology use. While the results of this study could serve as benchmarks, this study should stimulate more investigations of the phenomena studied here, which might contribute to the refinement of measurement techniques and results.

Further investigation should be carried out to understand how hard and soft technologies enhance the effect of each other on a localized basis, as well as on a factory-wide basis. Finally, the largest body of literature in manufacturing technology deals with technology justification; the findings of this study must be translated into specific implications for technology justification. For example, how much credit should be given to improvements in shop floor JIT, product line breadth, and growth and profitability, while justifying investments in technologies; this deserves investigation.

Based on the findings here, tools and methods that increase the *skilled use of manufacturing technology* deserve more investigation. Adler [2] notes that "the myth of deskilling" falsely encourages managers to expect that "new generations of equipment have permitted and will permit reductions in skill requirement. This myth is a major obstacle to effective planning for the implementation of new technologies." The reason why new manufacturing technologies require more skill, and not less, is that the nature of work associated with new technologies has expanded 1) worker responsibility; 2) the abstraction of tasks; and 3) the interdependence of tasks [2]. In this context, for the effective implementation of new process technologies, Adler recommends "new and broader type of training," and Meredith [26] found in his study of manufacturing technology implementation that "all-around education of everyone involved was a major factor in the successful implementation of new technologies."

This study's findings based on the perception of top management are favorable to investments in soft technologies. As a next step, researchers should use objective measures of SFPER, PLB, and strategic performance, and confirm the important findings of this study.

APPENDIX I
GLOSSARY OF MANUFACTURING TECHNOLOGY TERMS ADAPTED FROM [31]

Hard Technologies

1) Automated Guided Vehicles (AGVs): AGVs are unmanned carriers or platforms that are controlled by a central computer that dispatches, tracks, and governs their movements on guided loops. AGVs are primarily useful for materials handling, or between work stations as a replacement for conventional forklifts and transfer lines.
2) Automated Inspection (AI): Automated inspection is defined as the automation of one or more steps involved in the inspection procedure.
3) Computer-Aided Design (CAD): CAD is a computer software and hardware combination used in conjunction with computer graphics to allow engineers and designers to create, draft, manipulate, and change designs on a computer.
4) Computer-Aided Manufacturing (CAM): CAM incorporates the use of computers to control and monitor several manufacturing elements such as robots, CNC machines, and automated guided vehicles.
5) Computer-Integrated Manufacturing (CIM): CIM involves the total integration of all computer systems in accounting, engineering, production, etc., in a manufacturing facility; the integration may extend beyond one factory into multiple manufacturing facilities in one or more countries and into the facilities of vendors and customers.
6) Computer Numerical Control (CNC) machines: CNC machines are locally programmable machines with dedicated micro or minicomputers. CNC provides great flexibility by allowing the machine to be controlled and programmed on the floor.
7) Flexible Manufacturing Systems (FMSs): A flexible manufacturing system is a group of reprogrammable machines linked by an automated material-handling system and a central computer. The intent of such a system is to produce a variety of parts that have similar processing requirements with low setup costs.
8) Local Area Networks (LANs): LANs are the backbone of communication systems that connect various devices in a factory to a central control center. The LAN, through the control center, allows for the various devices connected to the network to communicate with each other.
9) Robots: The Robotics Institute of America defines the industrial robot as "A programmable, multifunctional manipulator designed to move material, parts, tools, or specialized devices through various programmed motions for the performance of a variety of tasks." The basic purpose of the industrial robot is to replace human labor under certain conditions.

Soft Technologies

1) Just-In-Time (JIT) Manufacturing: The concept of just-in-time manufacturing is a philosophy that requires materials and goods to arrive "just-in-time" to be used in production or by the customer. The philosophy of JIT has imbedded in it a "continuous habit of improving" and the "elimination of wasteful practices."
2) Manufacturing Cells (MCs): A manufacturing cell is composed of a small group of workers and machines in a production flow layout, frequently a U-shaped configuration, to produce a group of similar items called "part families" in dedicated production areas. Proponents of cellular manufacturing have claimed several benefits for this type of production system, including less inventory, less material handling, improved productivity and quality, improved worker job satisfaction, smoother flow, and improved scheduling and control.
3) Materials Requirements Planning (MRP or MRP I): MRP I is primarily a scheduling technique, a method for establishing and maintaining valid due dates or priorities for orders using bills of material, inventory and order data, and master production schedule information as inputs.
4) Manufacturing Resource Planning (MRP II): Manufacturing resource planning is a direct outgrowth and extension of closed-loop materials requirements planning (MRP) through the integration of business plan, purchase commitment reports, sales objectives, manufacturing capabilities, and cash flow constraints.
5) Statistical Quality/Process Control (SQC/SPC): SQC/SPC apply the laws of probability and statistical techniques for monitoring and controlling the quality of a process and its output. SQC/SPC can be used to reduce variability in the process and output quality.
6) Total Quality Management (TQM): TQM is built on the principle of continuous quality improvement in manufacturing, as well as the entire organization. It works well with frequent feedback of performance measures to various system elements empowered to make changes in their operation such that the system moves closer and closer to its stated goals.

APPENDIX II
DATA COLLECTION

Sample

This is a study of individual manufacturing **plants**, **not** a study of manufacturing **firms**. The survey questionnaire was sent to 4453 member firms of the National Association of Manufacturers (NAM) in the SIC industrial classifications 3400 through 3899 (followed by one reminder three weeks later in July 1993).

Split Sample

To examine the validity of the study, we developed a split sample. After mailing the questionnaire and one reminder, we received 556 usable responses; this formed the first "half" of the split sample. To increase the responses and to acquire the second "half" of the sample, instead of sending a mere reminder in the form of a card, we again sent the entire questionnaire again to

TABLE IV
STATISTICS FOR THE SPLIT SAMPLES

	Sample 1	Sample 2	Total
Sample size (n)	556	565	1121
1. Sales ($000,000)*	38.4 (n=487)**	56.4 (n=465)	47.2 (n=952)
2. Employment*	251.4 (n=513)	203.5 (n=502)	227.7 (n=1015)
3. Sales/employee ($000)	130.5 (n=484)	136 (n=460) 133 (n=944)	
4. Rejection (%)	3.92	4.07	4.00
5. Inventory turns	7.61	8.16	7.89
6. Cost-of-goods-sold (% of sales)	.609	.605	.606
7. Product lines	22	25	24
8. Average lead-time (weeks)	7.2	7.2	7.2
9. Direct labor (hours)*	18.31	18.27	18.3

* Averages exclude outliers.
** Averages based on the number of firms (n) reporting.

TABLE V
DISTRIBUTION BY INDUSTRY

	BOC estimate for the U.S. (firms with 20+ employees) (percentage)	1994 NAM respondents (percentage)
SIC 34	31.6%	42.5%
SIC 35	33.2	28.1
SIC 36	16.6	15.7
SIC 37	9.5	8.8
SIC 38	9.1	4.9
	100.1%	100%

those firms that did not respond to the first mailing. We also followed this with a reminder card. The second "half" of the sample yielded 565 usable responses. Thus, the total usable response was $556+565 = 1,121$; 25 responses were unusable and three responses came after 2-15-94, the cutoff date; the resulting response rate being 25.8%.

In Table IV, we present the averages for nine major *demographic* variables from the two samples for comparison. The similarity of the averages is an indication the lack of significant bias in the total sample. **All subsequent analyses were performed by pooling the two split samples into one pooled sample of 1121.**

Data Validation

Industry: The industries covered by this study are identical to those covered by a Bureau of Census (BOC) study published in 1993.[3] In Table V, we compare the distribution of plants by SIC classification with the BOC study serving as the reference. Table V shows that the distribution of manufacturing establishments in the U.S. is roughly comparable to the distribution of the respondents to this study with a slight bias toward SIC 34 (metal fabrication industry) in the NAM sample. This slight skewing toward one industry may be due to the slight bias toward larger plants in the NAM sample.

[3]U.S. Bureau of Census, *Manufacturing Technology: Factors Affecting Adoption 1991*, AMT/91-2, Current Industrial Reports, Government Printing Office, 1993.

ACKNOWLEDGMENT

The authors are grateful to H. Jerome, M. Kasetty, and C. Trimble, Graduate Research Assistants at the Thomas Walter Center, who assisted with database creation, data analysis, and figures.

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